Boundary Choices in Innovation:

How does the Availability of Hiring Affect Firms' Technology Sourcing Strategies?

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ABSTRACT

In this paper, I study the relationship between hiring and external technology sourcing. Hiring can either substitute for external technology sourcing by bringing new technologies/capabilities to a firm or complement external sourcing by providing information for evaluating and integrating external technology sources. The ability to transfer not only technologies but also technical capabilities further determines the differences in firms' external technology sourcing via the market for firms versus the market for technology. The empirical analysis employs a difference-in-differences causal inference design using staggered adoption of the inevitable disclosure doctrine (IDD), a state level law in the U.S. The results support the importance of hiring and demonstrate that when the external supply of technical labor is low, there is a substitution effect with external technology sourcing through the MFF but not the MFT. The substitution effect is more pronounced in states that have higher noncompete enforceability.

Keywords: hiring, technology-sourcing strategy, technical capability, market for firms, market for technology

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INTRODUCTION

One of the fundamental questions for strategic management and technology innovation scholars is whether firms develop internally or externally to achieve the strategic renewal of capabilities and innovation (Agarwal & Helfat, 2009; Arora, Cohen, & Walsh, 2016; West & Bogers, 2014). The existing literature has identified different modes that firms use to acquire technologies and capabilities and the factors that govern their selection of different modes (Arora et al., 2016; Capron & Mitchell, 2009; Mitchell & Shaver, 2003; Moeen & Agarwal, 2017). Although the literature on technology sourcing often treats internal innovation as the default option, there is a sharp distinction between innovation developed by existing employees (Tripsas, 1997) and innovation by newly hired inventors (Zucker & Darby, 1997), where hiring often provides the basis for more extensive innovation. However, the hiring option is not always available due to its reliance on external labor supply and legislative changes that affect this supply (Klasa, Ortiz-Molina, Serfling, & Srinivasan, 2017; Younge, Tong, & Fleming, 2015). However, we have only limited understanding of how the supply of technical labor via hiring affects firms' choices of other modes of external technology sourcing. In this study, I consider hiring to be an alternative to other modes of technology sourcing and study how the external supply of technical labor affects firms' external technology sourcing strategies.

Hiring new inventors brings firms both technical knowledge and technical capabilities for innovation, which could potentially be substituted by external technology sourcing. In addition, hiring is likely to complement external technology sourcing because it provides absorptive capacity (Cohen & Levinthal, 1990) and valuable insider information that lower the cost for target selection and integration. As external sourcing methods, the MFT and MFF differ in what opportunities they create for firms. The MFT, including licensing, patent right reassignment, or other types of transactions provides firms with new technology (Arora, Fosfuri, & Gambardella, 2001). By contrast, acquiring another company via the MFF provides a combination of technology and technical capabilities (Mitchell & Shaver, 2003). When the external supply of employees is constrained, firms can substitute this supply with either the MFF or the MFT to obtain codified technical knowledge, but they can only substitute it with MFF to obtain technical capabilities.

In the empirical analysis, I explore the relationship between the supply of external employees and firms' reliance upon the MFF and MFT to source external technology and capabilities. I employ a difference-in-differences causal inference design, based on staggered adoption of the inevitable disclosure doctrine (IDD). The IDD is a legal doctrine to protect firms' trade secret by preventing its employees from moving to competitor firms, by different states in the US to identify exogenous changes in the supply of employees (Klasa et al. 2014).

The findings suggest a substitution effect between hiring external employees and external technology sourcing through the MFF, but not the MFT. This is potentially due to the differences in their ability to source tacit technical capabilities and human capital. When the state level noncompete enforceability is high, the substitution effect is stronger compared to states with lower noncompete enforceability – which further supports the key argument that it is the ability of hiring new inventors from externally, rather than the implementation of IDD itself, that leads to the firms' substitution with external technology sourcing.

These findings advance our understanding of strategic resource development (Capron & Mitchell, 2009) and technology-sourcing strategies (Arora et al., 2016) by linking employee mobility (Mawdsley & Somaya, 2016) to external technology sourcing. Drawing upon the Build-Borrow-Buy framework (Capron & Mitchell, 2012), this study takes the new angle to distinguish between internal development carried out by new hires versus existing employees and shows how the ability to hire new employees affects firms' technology sourcing strategies. It is the first effort to match both patent filings and patent assignment data to the universe of U.S. manufacturing sectors while distinguishing between patents obtained through different channels.

The remainder of this paper is organized as follows: Section Two describes the theoretical background and hypothesis development; Section Three introduces the data generation process, the difference-in-difference framework, and the estimation methodology; Section Four presents the results; and Section Five provides a summary of the findings and a brief discussion.

THEORETICAL FRAMEWORK

Modes of technology sourcing

The existing literature on resource-based perspectives, dynamic capabilities, and strategic renewal suggests that firms commonly use a combination of different modes to renew their capabilities and maintain their competitive advantage (Agarwal & Helfat, 2009; Helfat et al., 2007). Firms use internal development to exploit existing resources and capabilities and use external sourcing to obtain new capabilities – which also help firms overcome obsolescence and inertia (Helfat, 1994, Rosenkopf & Nerkar, 2001; Vermeulen & Barkema, 2001). The choice that firms make regarding which mode they will use to develop new resources and renew their capabilities – internally or externally, through service contracts, alliances, or acquisition – is critical. A study of selective capabilities (Capron & Mitchell, 2009) reported that the choice of mode is dependent on a firm's capability gaps and internal social institutions. Lee and Lieberman (2010) demonstrated that the choice is also related to the distance of the new market from the firm's primary business domain.

The literature on the economics of innovation and technology management has also identified that firms use a variety of modes of technology sourcing and knowledge development, especially during periods of market creation and competence-destroying technological change. This phenomenon is largely captured in studies on open innovation (West & Bogers, 2014) and the division of innovative labor (Arora et al., 2016; Arora & Gambardella, 1994; Arora & Merges, 2004). For internal development, firms can either rely on existing inventors (Tripsas, 1997) or hire new human capital (Zucker & Darby, 1997). For external sourcing, firms can obtain technology through the MFT (Arora et al.,

2001) or the MFF (Higgins & Rodriguez, 2006; Mitchell & Shaver, 2003) or by forming strategic alliances (Rothaermel, 2001). Arora et al. (2016) demonstrated that approximately half of their survey respondents that generated new-to-the-market innovation indicated having used external technology sources for their innovation. The prevalence of combining internal and external sources of innovation has also been identified in other studies (Kapoor & Klueter, 2015; Moeen & Agarwal, 2017; Rothaermel & Thursby, 2007).

The above two streams of literature have different views regarding internal capability development. In the strategic management literature, internal development is path dependent (Cohen & Levinthal, 1990; Kraatz & Zajac, 2001; Penrose, 1959) and exploitive (Helfat, 1994; Stuart & Podolny, 1996). External sourcing enables firms to search distantly, overcome the inertia pressure associated with an internal search (Rosenkopf & Almeida, 2003), and reach beyond a larger capability gap (Capron & Mitchell, 2009). According to the technology innovation literature, it is possible to adopt new technologies and to obtain technical capabilities by hiring new inventors during periods of technological change (Zucker & Darby, 1997). However, scholars have rarely distinguished between internal innovations developed by existing inventors versus those developed by newly hired inventors (e.g., Arora et al., 2016; Cassiman & Veugelers, 2006). In parallel, we do not have a comprehensive understanding of the importance and strategic value of hiring in helping firms to gain new technology.

Importance of hiring during new technology development

Strategy and technology management scholars have devoted a great deal of effort to document and explain the inability of incumbent firms to adapt to technology changes

(Christensen, 1997; Henderson & Clark, 1990; Tripsas, 1997; Tripsas & Gavetti, 2000; Tushman & Anderson, 1986). One common challenge faced by incumbent firms is that they suffer from inertia in their technology bases, organizational routines, investment strategies or consumer bases (Hill & Rothaermel, 2003). Such organizational inertia imposes a real burden on firms during technological change – which often requires changes in operating procedures and even the underlying knowledge base.

One way in which firms sustain through technological changes is by developing new skills, which can be achieved either by educating existing employees or by hiring new employees with new skills (Tripsas, 1997; Zucker & Darby, 1997). Two prominent examples of technological changes are nanotechnology and biotechnology (Rothaermel & Thursby, 2007). Based on a sample of U.S. manufacturing firms (Figure 2) adopting nanotechnology or RNAi (RNA interference, a novel technique in biotechnology), firms that innovate using these new technologies are likely to have new inventors who joined the firm later to work on these new technologies compared to the firm's average set of inventors. If a firm's initial mode of adopting the new technology is through an external source, then its internal development is likely carried out by inventors who joined the firm even later. Additionally, based on inventor-firm matched data, an inventor's average patent life associated with a firm is approximately six to seven years (Table 3) – which is true for both average firms and the subset of firms that adopted nanotechnology or RNAi.

Insert Table 3 about here

These lines of evidence from the prior literature and from examples of technological changes suggest that hiring is important for firms' innovation activity. In particular, as firms attempt to develop new technologies, hiring can help them to obtain the necessary technical capability and knowledge to achieve this goal. The specific feature of hiring in developing new technology suggests that it might be an alternative to other modes of external technology-sourcing strategies such as the MFF, the MFT, and alliances. In this study, I study the relationship between the external supply of technical labor and external technology-sourcing activities, focusing on the MFF and the MFT.

Hiring and external technology sourcing: substitutes or complements?

The employee mobility literature frequently discusses organizational outcomes of the inter-organizational movement of personnel. Employee movement brings benefits to the receiving firms in innovation (Rao & Drazin, 2002; Song, Almeida, & Wu, 2003), including learning (Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011), capability acquisition and divestiture (Agarwal, Echambadi, Franco, & Sarkar, 2004). Employee mobility transfers both human capital and relational capital, which means that the receiving firms obtain new skills, knowledge, or relationships, whereas the losing firms either lose valuable assets or benefit from new relational capital (Mawdsley & Somaya, 2016). One of the most prominent benefits of employee mobility arises for innovation and spillovers of technological knowledge, where different types of valuable assets are transferred during the process. These valuable assets include tacit knowledge that underlies the technologies invented by the source firm (Tzabbar, Aharonson, & Amburgey, 2013), key routines that help recipient firms develop new technology trajectories (Song et al., 2003; Tzabbar, 2009), and external information networks that help enhance absorptive capacity (Cohen & Levinthal, 1990). The benefit for the recipient firms' subsequent innovation has been documented by patent citation patterns (Rosenkopf & Almeida, 2003; Song et al., 2003).

By default, employees are free to quit their employers (Coff, 1997), and firms can hire whoever they want. However, various constraining factors impede this process – and here I focus on supply-side factors. The total supply of human capital that has the necessary knowledge and skills is one important concern for the supply of labor. This is also true for the early stage of technological changes when there are not many skilled labors in the labor market. In addition, valuable human capital may already be involved with other companies and are not willing to move. Even if they do, there are many policy or legislative procedures that restrict their ability to move, such as the non-compete clauses or the Inevitable Disclosure Doctrine (Klasa et al., 2017; Younge et al., 2015). Thus, firms may frequently face the problem of efficiently sourcing human capital due to supply-side constraints.

When employee mobility is compromised, firms can use alternative routes to benefit without hiring new talent, including network and geographic knowledge spillovers, acquisitions, and alliances (Mawdsley & Somaya, 2016). For example, acquisition has long been recognized as a viable mechanism for interfirm learning, knowledge transfer, and capability reconfiguration (Ahuja & Katila, 2001; Karim & Mitchell, 2000; Song et al., 2003; Younge et al., 2015). Recent developments in this literature have also investigated the new phenomenon of "acqhires" (Chatterji & Patro, 2014; Coyle & Polsky, 2013). Similarly, strategic alliances bring firms opportunities to exchange knowledge and resources; representing an alternative to bringing in new employees (Hamel, 1991; Inkpen, 1998; Kale & Singh, 2007).

Connecting the employee mobility literature to the technology-sourcing context, the employee mobility literature implies that hiring new inventors is potentially a substitute to other modes of technology sourcing – although the innovation output that we actually observe is in the form of an internal patent. Consequently, when inventor mobility is constrained, in order to access new technology, firms may pursue external technology sourcing as a substitute.

H1. (Substitution) The lower the supply of external employees, the more likely that firms will obtain technology from external sources.

Now consider an alternative argument to H1. The literature examining the relationship between internal and external sources of technology sourcing has suggested internal knowledge sourcing and external knowledge sourcing complement one another (Cassiman & Veugelers, 2006; Love, Roper, & Vahter, 2014). There are different factors that condition the level of complementarity (Grigoriou & Rothaermel, 2017), including absorptive capacity (Cohen & Levinthal, 1990), intellectual property, the type of research and development conducted (Cassiman & Veugelers, 2006), the types of experience in different learning stages (Hoang & Rothaermel, 2010), and internal knowledge network properties (Grigoriou & Rothaermel, 2017). This literature suggests that, due to the high uncertainty and risk in conducting and contracting for innovation, the sourcing firm requires the ability to properly evaluate external technology during the external sourcing process (Cohen & Levinthal, 1990). Newly hired inventors contribute to the firms' internal innovation workforce and technical capabilities; they are a valuable source of the firms' absorptive capacity that potentially facilitate the firms' external technology-sourcing activities to help them understand and evaluate external technology.

In addition, external employees have valuable insider information about their original employers – either a potential target for the MFF or a potential supplier for the

MFT. This valuable insider information can be important for resolving the information asymmetry problem (Akerlof, 1970; Ragozzino & Reuer, 2011) during technology sourcing and lower the cost for subsequent integration. As a result, firms are likely to choose their targets for external technology sourcing from among firms that have previous ties with their hired employees. Thus, when inventor mobility is constrained, firms are likely to perform less external technology sourcing.

H2 (alternative to H1). (Complement) The lower the supply of external employees, the less likely that firms will obtain technology from external sources.

In this study, I consider two different types of external technology sourcing, the MFF, and the MFT, and test on the hypotheses separately.

Additional notes on the differences between the market for firms and the market for technology

There is a whole spectrum of choices that firms may pursue during external sourcing, ranging from the more integrated approach such as the parent-subsidiary relationship to pure arm's length market transaction (Rothaermel, 2018). Lying in the middle of this make-or-buy continuum are different types of strategic alliances, including short-term contracts, licensing, franchising, equity alliances, and joint ventures. For ease of analysis and interpretation, in this study, I focus on the two extremes on the make-or-buy continuum: the market for firms, and the market for technology represented by the full reassignment of property right.

The different modes of external technology sourcing vary in the content delivered. There are two types of technological knowledge: codified technical knowledge and tacit technical capabilities (Nelson & Winter, 1982; Winter, 1987). The MFT transfers codified technical knowledge through arms-length transactions, which are largely promoted with efficient patent protection (Arora & Ceccagnoli, 2006). However, it is harder to transfer tacit technical capabilities through the MFT (Arora & Gambardella, 1994; Kogut & Zander, 1992; von Hippel, 1990; Winter, 1987). On the other hand, the resourced-based view considers the firm to be a bundle of resources and assets (Barney, 1986; Wernerfelt, 1984), and the resource base can be changed or modified through its dynamic capability (Helfat et al., 2007). By acquisition, firms can obtain important resources and capabilities to achieve further growth (Capron, Dussauge, & Mitchell, 1998). This point is especially true for technological acquisitions in which an acquirer obtains access to the target firm's knowledge base and technological capabilities (Ahuja & Katila, 2001). Acquisition enables the firm to access the target firm's specific know-how (O. Bertrand, 2009) and is more appropriate than other modes of technology sourcing when the underlying knowledge is tacit (Ranft & Lord, 2002). Thus, technology sourcing through the MFF grants the acquiring firm both codified technical knowledge and tacit technical capabilities associated with the target firm.

When firms have difficulty hiring new inventors, they are lack of both new technical knowledge and the tacit technical capabilities. Even though both the MFT and the MFF can provide new technical knowledge, only the MFF is able to provide the underlying tacit technical capabilities. Thus it is expected that firms' response in external technology sourcing through the MFF and the MFT would be different under this condition – namely, the MFF may be more responsive to a constraint in hiring new inventors.

DATA AND METHODS

Sample

The sample for this study is drawn from the 2013 National Establishment Time Series (NETS) database. The NETS database is developed by Walls & Associates by combining the Dun and Bradstreet (D&B) archival establishment data into a time-series database that contains establishment level information in the US. A snapshot of the D&B data is taken every January from the full Dun Marking Information file, and no establishments are deleted from the database. Even though the NETS database has not been used widely in the strategic management literature, it is based on the same source data (D&B) data for the Bureau van Dijk Orbis Database prior to 2013. And the Orbis database has been used in the strategic management literature (Arora, Belenzon, & Rios, 2014). Thus, the NETS database is a comprehensive database that provides annual records for a large part of the US economy. It provides easy access to track the changes in each establishment across different years. Especially, it provides ownership information (similar to Orbis) and ownership changes that help identify establishment level acquisition.

Each firm is defined as an active headquarter firm recorded in 2010, from which I draw information on its M&A activities and other information. The 2010 headquarter firms are further grouped if the firms had the same firm name – representing the same firm under the same larger corporate group. The grouping of firms follows a similar procedure as the patent matching process (see the Data Appendix for further details), which is based on firm name string matching. If two firms have the same name, then the matching process did not distinguish between the two. Because this study focuses on U.S. manufacturing firms, universities and banks are eliminated from the sample by a word search of “UNIV,” “COLLEGE,” or “BANK.” These institutions are eliminated because universities have a different patenting strategy from industrial companies (Trajtenberg, Henderson, & Jaffe, 1997), whereas banks have numerous patent assignment activities as collateral (Marco, Myers, Graham, Agostino, & Apple, 2015), both of which are irrelevant to this analysis.

As described in the Data Appendix, the firms are linked to the United States Patent and Trademark Office (USPTO) patent and patent assignment data by firm name string matching. In addition, patents are categorized as internal patents (developed internally and having the original firm as the assignee), MFT patents (developed by another party and reassigned to the firm), or MFF patents (obtained through M&A). The year for internal patents is defined as the year of filing. The year for MFF or MFT patents is defined as the year that the acquisition or deal is made. See Figure 1 for the aggregate year trend for each of the patent types. This matched dataset is linked to the Harvard Patent Inventor Dataverse (Li et al., 2014), which provides further information on inventors and their locations.

Insert Figure 1 about here

Because the IDD treatment in this study is at the state level, the resulting treatment effect is also assessed within the boundaries of a state. I further assign patents to individual establishments based on the minimum distance between the patent inventor and the establishment. The sample is further eliminated to focus on patents that are at the same state as the matched firm establishment.

The time frame for the sample is from 1991 to 2010. I only look at headquarter firms that are active throughout the whole time period to eliminate the unexpected effect of firm entry and exit on the measurement of external technology sourcing. That way, this study focuses on a relatively stable sample of firms and looks at their firm-level strategy in patenting, acquisition, and their involvement in the market for technology. A firm is included only if there is at least one patent (that could be from any of the three types of patent) matched to the firm during the matching process.

The empirical analysis is at the firm-state-year level. Because a firm can operate in different states at different time, they do not necessarily have any patenting or external technology sourcing activity in that state during a certain time period. So for each firm-state, its "real active period" is defined as from the year it has its first matched patent until the year it has its last matched patent. If no patent is matched for years between the first and last year, the firm-state-year is still included as an observation, and the number of patents is set to zero for all three types of patents. For time periods that are outside this "real active period", the observations are excluded from the final sample.

The final sample consists of 16,464 firms, and 206,400 firm-state-year observations. See Table 1 for the summary statistics and correlation matrix.

Insert Table 1 about here

Dependent variables

Number of MFF patents: The total number of MFF patents (obtained through M&A) is generated at the firm-state-year level, representing the level of external technology-sourcing activities through the MFF within the state each year. The variable is log-transformed to approximate a normal distribution.

Number of MFT patents: The total number of MFT patents (obtained through the market for technology) is generated at the firm-state-year level, representing the level of external technology-sourcing activities through the MFT within the state each year. The variable is log-transformed to approximate a normal distribution.

Independent variables

IDD (treatment variable): IDD is an indicator variable that equals one if the state had the IDD in place that year. The information for the state adoption and rejection of the IDD was based on Klasa et al., (2017). See the next section for a discussion on the validity of using the IDD as the treatment.

Enforceability: In the last analysis, I also look at heterogeneous treatment effects by categorizing the sample into high and low noncompete enforceability based on Starr (2019).

Control variables

Whenever applicable, firm age is calculated based on the year of establishment for the headquarter firms. Firm total patenting is calculated based on the internal patents of the matched patent sample. Firm sales and total employees are calculated each year and are thus controlled as a firm-level time-varying variable.

At the state level, following Flammer and Kacperczyk (2017), I include the noncompete index developed by Garmaise (2009) to control for the enforcement of noncompete clauses in the state.

See Table 5 for analysis based on different model specifications. The main analysis uses firm fixed effect, state fixed effect, and year fixed effect throughout this study. Robust standard errors are clustered at the state level throughout the analysis.

Insert Table 5 about here

Inevitable disclosure doctrine (IDD)

The IDD is a legal doctrine that protects a firm's trade secrets by eliminating employees' ability to work for a direct competitor of the firm. The IDD is applicable based on "threatened misappropriation," which suggests that as long as there is a threatened disclosure of the firm's trade secrets, the firm may ask state courts to prevent its employees from working for a competitor in similar positions. It applies to the state of an employee's original firm even if the potential new employer is in another state without the IDD (Garmaise, 2011; Klasa et al., 2017).

Difference-in-differences design

This study examines the state adoption of the IDD as the exogenous source of variation to study firms' technology sourcing behavior when employee mobility is low. A difference-in-difference methodology was utilized based on the 21 treatments listed in Klasa et al. (2017). For those states, a precedent-setting case became case law and represented the start date of the state court recognizing the IDD. For three of the states, IDD recognition was later reversed in a subsequent court decision. The IDD indicator equals one if the state court recognizes the IDD in the year and zero otherwise. For the other 29 states that never explicitly considered or rejected the IDD, the IDD indicator is equal to zero in every year. This study followed Bertrand and Mullainathan's (2003) methodology in the presence of staggered treatments at the state level and estimated the following regression:

$$Dep\ Var_{ist} = \alpha_i + \alpha_s + \alpha_t + \beta_E IDD_{st} + \gamma' \mathrm{X}_{ist} + \varepsilon_{ist}$$

where $i, s,$ and t index firms, the state, and the year, respectively; α_i, α_s, α_t, represent firm, state, year fixed effects, respectively. ε is the error term. Because the analysis at the level of external technology sourcing is based on count variables, I use Ordinary Least Square (OLS) with log-transformed count variables to estimate the coefficients. The coefficient of interest is β_E, which measures the effect of the IDD on the amount of externally sourced technology.

The validity of the identification strategy

To satisfy the relevance condition, the adoption of the IDD must result in changes in the level of employee mobility. Klasa et al. (2017) used the Census Bureau's Survey of Income and Program Participation to show that the recognition of the IDD significantly reduced the mobility of knowledge workers in possession of the firm's trade secrets. Studies have also shown that rejection of the IDD was correlated with an increase in the knowledge of workers' mobility (Png & Samila, 2015). These studies supported the relevance condition that with the presence of the IDD, employee mobility is lower; without the IDD, employee mobility is higher.

Further discussion on the validity of the treatment using IDD follows Athey and Imbens (2018). For the design assumption, the assignment of the treatment needs to be random, conditional on the potential outcomes and possibly pretreatment variables. In the data, there is no strong correlation between the state level IDD assignment and the innovation activities, including internal patenting and external patenting of the firms.

For the exclusion restriction, the identification strategy assumes that the adoption of the IDD was exogenous regarding firms' innovation and technology-sourcing strategies. I now discuss why this assumption is likely to be valid. The adoption of the IDD at the state level is not based on state laws that could be influenced by lobbying. Instead, it is based on specific precedent-setting cases driven by the merits of the involved companies and the final judicial decision. Because of the potential significant harm to a firm upon the loss of trade secrets, state courts often make decisions on precedent-setting cases quickly, which makes it difficult for the average firm to anticipate this change ex-ante. The main purpose of judicial decisions involving the IDD is to balance employers' interests in protecting trade secrets and the public policy concern regarding employee mobility and freedom of employment (Godfrey, 2004; Harris, 2000), and it is less likely to be affected by individual firms' technology-sourcing strategy. When IDD is adopted, all firms in the state are exposed to the restriction imposed by IDD, and it does not matter how long the adoption has happened. Thus satisfies the second assumption by Athey and Imbens (2018).

The staggered treatment allowed the eventually treated firms to be in the control group first and in the treatment group later. This treatment also allowed me to run the regression analysis using only the eventually treated firms – which is consistent with the main analysis and the hypotheses.

Alternative analysis based on matched sample

The identifying assumption in the difference-in-difference design is that, without the IDD, the average technology-sourcing activity in the treated and control groups follows a parallel trend before and after the IDD. This issue raises a concern about the comparability of the control and treated states as a whole and calls for the importance of matching firms in the treatment group with appropriate counterparts in the control group while executing the difference-in-difference research design. Thus, I further utilize the propensity score matching (PSM) methodology to create relatively balanced treatment and control groups to estimate the treatment effect.

PSM is the most common "clone-finding" method, (Hirano, Imbens, & Ridder, 2003; Imbens & Rubin, 2015). The estimation of the propensity score is based on firm characteristics including year of establishment, total internal patenting, current year sales and employment, and state status for other noncompete clauses. The estimation equation controls for the same set of covariants. The final estimation model uses inversed propensity weighting.

RESULTS

Baseline analysis at the state-year level

The logic underlying my argument is that firms have incentives to hire new inventors to innovate using new technologies during technological changes (Tripsas, 1997; Zucker & Darby, 1997), yet sometimes face constraints on their ability to hire. Drawing on the literature on employee mobility and technology sourcing, I develop competing hypotheses concerning whether constraints on hiring lead to greater or lesser external sourcing, depending on whether hiring new inventors and pursuing external technology sourcing are substitutes or complements. To test which of the complementary or substitution forces dominates, this study employs a difference-in-difference design utilizing the stepwise state adoption of the IDD to investigate the impact of employee mobility on firms' external technology sourcing. Specifically, I examine two different modes of technology sourcing: patents obtained through the MFF; and patents obtained through the MFT.

In the first step, I look at the aggregate changes in external technology sourcing in response to the IDD treatment at the state level. Figure 3 illustrates the average number of patents transferred through the MFF or the MFT at the state level in each year. Here I am only showing the states that eventually received the IDD treatment at some point, and all states are aligned to the year of initial IDD adoption. At the aggregate level, we can see that the number of patents transferred through the MFF or MFT is higher after the IDD treatment. The average level of MFF patent seems to be increasing several years before the treatment, but stays the same in the year before the treatment. The average level of MFT patent seems to be flat and does not have much change before the treatment.

Insert Figure 3 about here

Table 4 shows the regression analysis at the state-year level after controlling for the state level internal patenting and the state fixed effect. Robust standard errors are clustered at the state level. Columns (1) and (2) look at technology sourcing through the MFF, and Columns (3) and (4) look at technology sourcing through the MFT. Based on this analysis, there is a significant increase in patent transferred through both the MFF and the MFT upon the treatment of IDD. There is about 25 percent increase of the MFF patent, and 57 percent increase of the MFT patent at the state level.

Insert Table 4 about here

Additional evidence is also available based on the patent licensing records from the KtMine data. See Figure 4 for a comparison of the number of licensed patents with and without IDD treatment.

Insert Figure 4 about here

Treatment effect on external technology sourcing at the firm-state-year level

In order to understand the firm-level changes in technology sourcing strategy, in the next step, the analysis of the treatment effect of IDD on external technology sourcing is assessed at the firm-state-year level. Table 6 shows regression analysis at the firm-state-year level, with dependent variables measuring the count of patents obtained through the MFF (columns 1 to 3) or the MFT (columns 4 to 6). This model includes year fixed effect, state fixed effect, firm fixed effect, and several time-variant firm-level variables. It also includes the non-compete index to control for the state level non-compete implementation.

Insert Table 6 about here

From this analysis, we can see that upon the IDD treatment, there is on average a 1 percent increase in the amount of MFF patent. It suggests that firms are more likely to acquire other companies to obtain technology when facing constraint in hiring new inventors. As discussed in the theory section, this can be explained by firms' incentive to obtain new technology from externally when hiring is not easy, and also reflects the fact that firms acquire other companies to obtain their human capital and technical capabilities. For the MFT patents, there is not a significant treatment effect on either substitution or complementarity. This is potentially due to the need to obtain technical capabilities, that firms are not able to achieve through the MFT. The treatment effect also holds when the analysis is performed based on the sample of the states that eventually received the treatment (columns 3 and 6).

In conclusion, the main analysis suggests there is a substitution effect for the MFF, but not for the MFT.

Heterogeneous treatment effect based on state noncompete enforceability

The IDD is essentially one special type of noncompete clauses. Unlike most of the other non-compete clauses that are written in the employment contract, the IDD is not written in a contract and is applicable as long as there is threatened disclosure of the firms' trade secrets. Yet the IDD essentially provides an option to sue potential moving employees, and its enforceability is largely based on the employer's willingness to pursue a lawsuit. Thus the state level noncompete enforceability is relevant here because it is correlated with how difficult it is to hire new inventors when IDD is present. When IDD is adopted in a state, if the noncompete enforceability is high, then firms in the state are more likely to challenge potential employee movement, thus the treatment effect is expected to be higher. Conversly, if the noncompete enforceability is low, then the treatment effect is expected to be lower. Based on Starr's (2019) noncompete enforceability scores, I categorize the states into high and low enforceability and analyze the treatment effect of IDD separately.

In Table 7, the same regression analysis is performed on the two subsamples representing high or low level of noncompete enforceability. In columns 1 and 2, there is a 1 percent increase in the level of MFF patents when noncompete enforceability is high, but not a significant increase when the noncompete enforceability is low. Although the magnitude of the treatment effect is the same in high-noncompete enforceability states, the significance level is much higher. The result suggests that noncompete enforceability seems to have a strong impact on firms' technology sourcing activities through the MFF. When noncompete enforceability is low, firms expect that they can still hire away employees even when IDD is in place. Thus they have less incentive to obtain human capital through acquisition. In columns 3 and 4, there seems to be no significant treatment effect for the MFT patents, no matter the noncompete enforceability is high or low. Having IDD in place itself may not be necessary for firms to be willing to substitute with external technology sourcing. It is the fact that firms are facing difficulty in hiring new inventors that encourages them to pursue more external technology sourcing, and especially through acquisition.

Insert Table 7 about here

Treatment effect estimation based on the matched sample

Due to the common concern on the imbalance between the control and treatment groups in the difference-in-difference analysis, especially when considering firms located in different states, I further use the PSM approach to create matched sample. The resulting sample has better balance between the two groups, thus provides better estimation of the treatment effect.

In Table 8, the analysis is performed on the matched sample after PSM. Columns 1 to 3 look at the MFF patents, and columns 4 to 6 look at the MFT patents. In column 1, the matched sample shows an even stronger treatment effect supporting the substitution effect. There is on average 2 percent increase in the level of external technology sourcing through the MFF, which is stronger both in the magnitude and in the significance level compared to the original analysis based on the whole sample. The treatment effect is stronger in states with high noncompete enforceability (column 2), and is weaker in states with low noncompete enforceability (column 3). For the MFT, the matched sample also did not show any significant treatment effect.

Insert Table 8 about here

CONCLUSIONS AND DISCUSSION

Although there are different choices of modes for external technology sourcing (Arora et al., 2016; Grigoriou & Rothaermel, 2017; Kapoor & Klueter, 2015; Moeen, 2017), there are also different ways of conducting internal innovation (Hill & Rothaermel, 2003; Zucker & Darby, 1997). This study suggests that hiring new inventors is one way in which firms can access new technologies and technical capabilities, thus being potential substitutes for other modes of external technology sourcing. In addition, hiring complements external sourcing because it brings absorptive capacity (Cohen & Levinthal, 1990) and insider information that facilitates the evaluation of external targets and subsequent integration.

This study focuses on two different modes of external technology sourcing: the market for firms (MFF) and the market for technology (MFT). The empirical analyses show that, when the external supply of employees is constrained, the substitution effect dominates and firms are likely to obtain new technology externally through the MFF, but not through the MFT. The difference between the MFF and the MFT is likely due to the differences between the MFF and MFT in sourcing technical capabilities.

This study incorporates patent reassignment information from the USPTO and identifies three types of patents: internal patents, MFT patents, and MFF patents. It represents an advance in patent matching compared to that of prior studies (e.g., Arora, Belenzon, & Rios, 2014), and is the first large scale study to match the patent filing and reassignment information to the universe of U.S. manufacturing sectors. The large-scale matching of three different categories of patents enables me to study firms' technology-sourcing strategy in detail.

However, there are limitations to this study that provide opportunities for future research. First, this study does not examine the outcomes of these different types of technology-sourcing strategies, focusing only on firms' decisions to pursue them. Thus, we do not know whether the compensation for hiring by external technology sourcing results in better innovation outcomes. Second, I focus on U.S. patenting activities and within the same state in which the acquiring firms operate. Firms may also have considerable technology-sourcing and talent acquisition activities outside the state or even on a global level, but in the empirical analysis of this study, I only consider patents within the same state of the establishment.

This study opens avenues for future studies. While hiring an employee almost always have lower costs than acquiring a company, is hiring always the optimal choice that firms pursue? Or, when firms are facing the different choices between internal versus external, which is the optimal strategy? In this study I do not look at hiring activities specifically, but only assess the ability of hiring through the state adoption of IDD or the state noncompete enforceability. A further understanding of these problems will create a more concrete picture of firms' technology-sourcing strategies.

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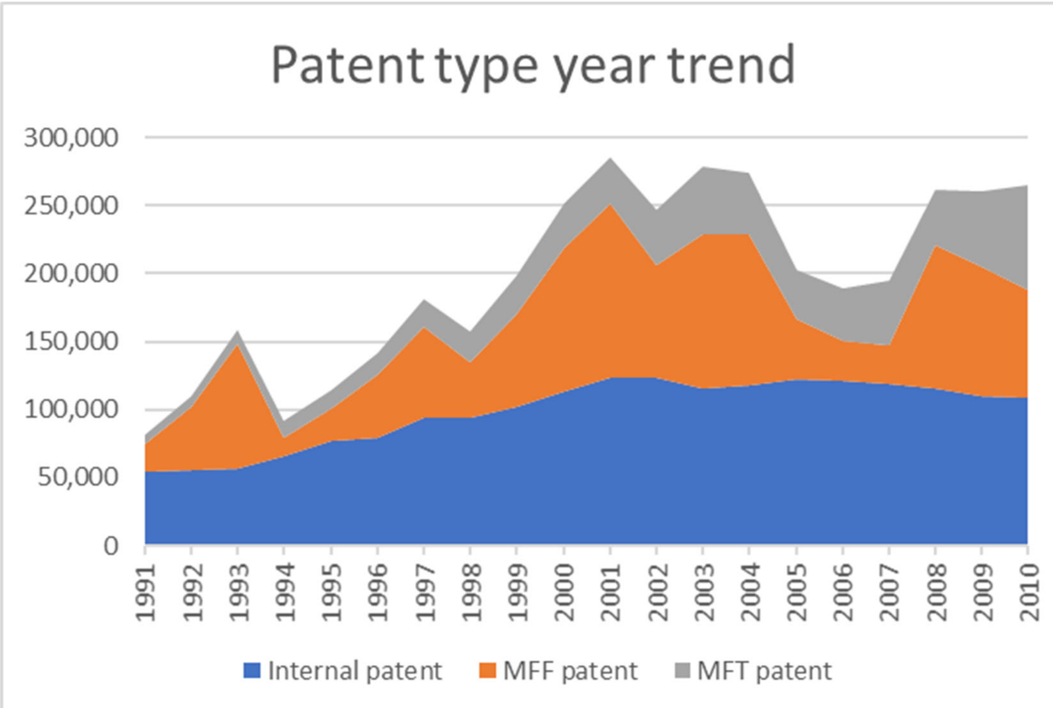
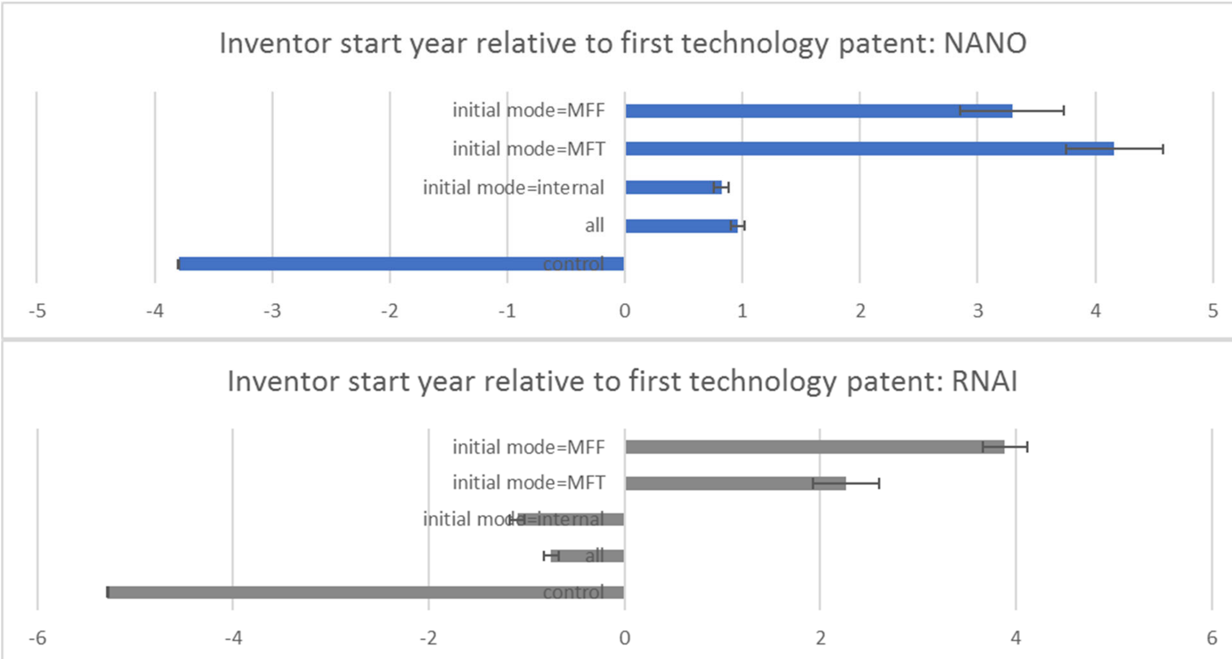
TABLES AND FIGURES

Figure 1. Aggregate patent year trend by different types of patents



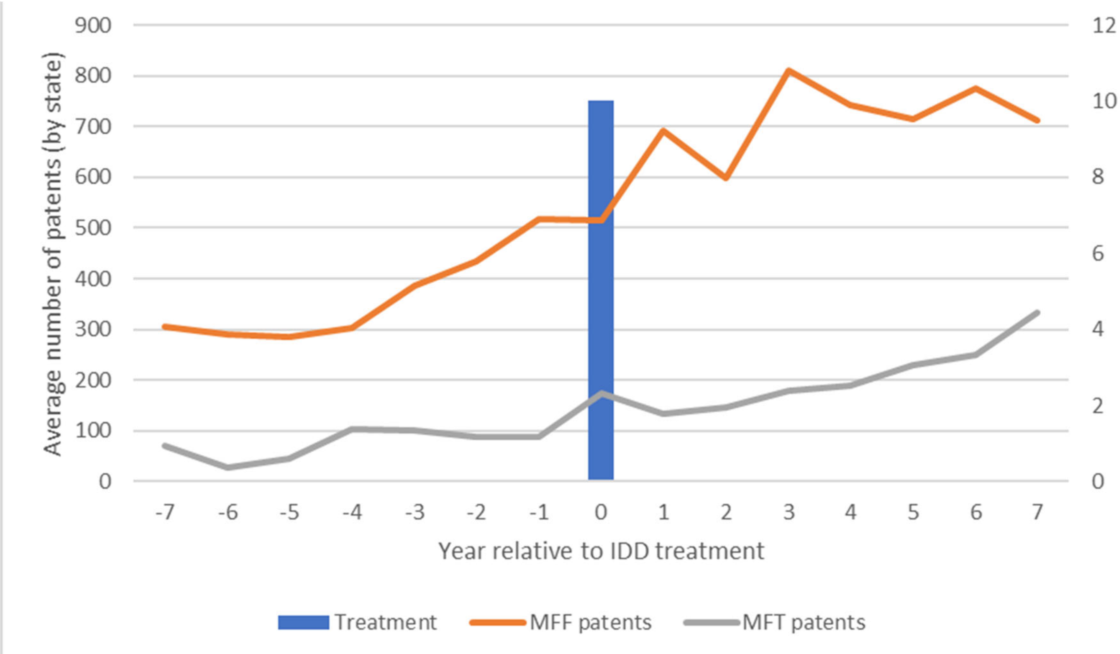
Note:
This figure shows the cumulative number of patents for each patent category each year, based on the sample of this study. Internal patents are the ones that the focal firm are the original assignee. MFT patents are the ones that are reassigned to the focal firm, but the original assignee is neither part of the focal firm, nor acquired by the focal firm. MFF patents are the ones that are initially assigned to another firm that is acquired by the focal firm.

Figure 2. Inventor start year and adoption strategy



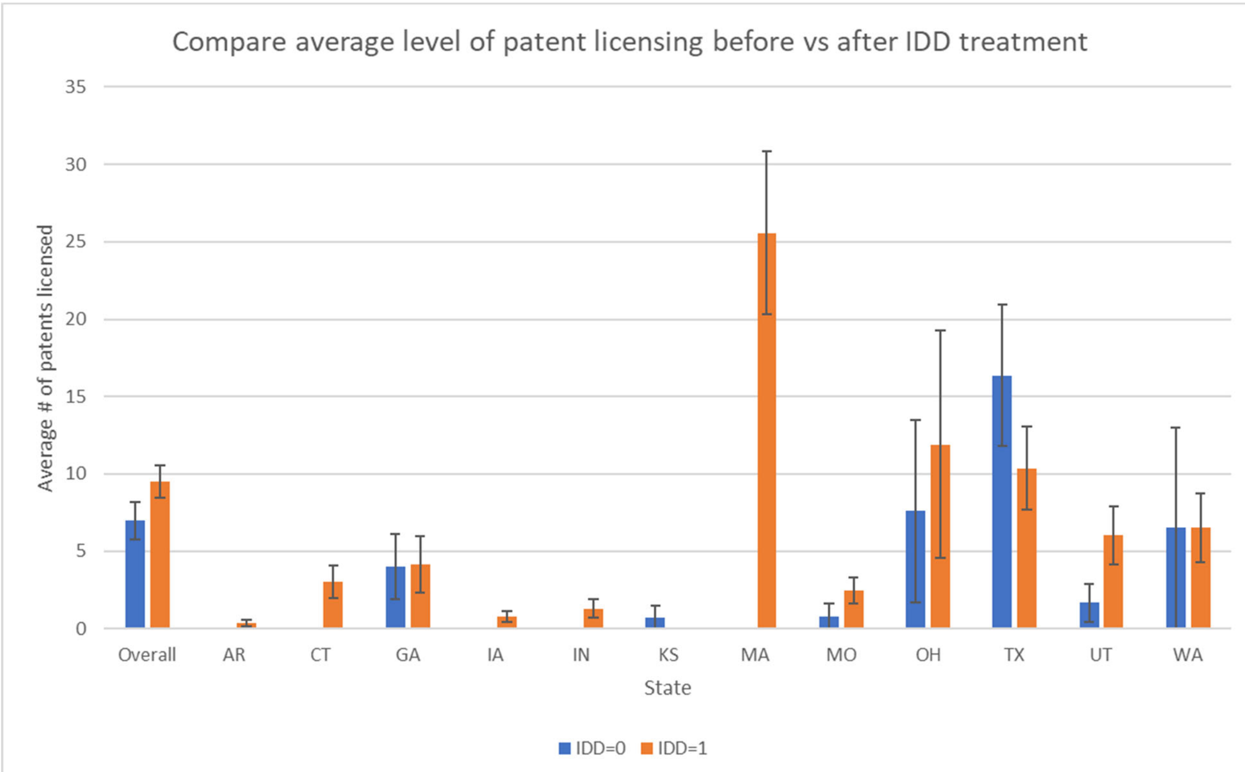
Note:
This figure shows two examples of technological change (Nanotechnology and RNAi) and the summary statistics on inventor start year for firms who adopted the new technologies.
In both figures, the X-axis is the year relative to technology adoption, with 0 means the first patent on the corresponding technology – no matter it is an internal, MFT, or MFF patent.
The figures show that the average inventors who did not work on the new technology joined the firm about 4 to 5 years before the technology adoption. The inventors who work on the new technology joined the firm around the time of technology adoption. If the initial mode of adoption is through an external source, the internal development of this technology is carried out by inventors that joined the firm even later.

Figure 3. Technology sourcing time trend (by patent count) for treated and control samples



Note:
This figure shows the pre- and post-treatment trend of external technology sourcing (by total patent count) in states that received the treatment in the middle of the sample period. 0 means the year the IDD treatment was adopted. All states that received treatment are aligned relative to the year of treatment; then the aggregate patent count is calculated and shown here.

Figure 4. Compare level of patent licensing before & after IDD treatment



Note:
This figure compares the pre- and post-treatment level external technology sourcing overall, and in states that received the treatment in middle of the sample period. Different from the main regression analysis, this figure is based on the KtMine data which documents licensing agreements. For each state shown above, the left bar shows the average number of patents transferred through licensing in the years that the state does not adopt IDD, and the right bar shows the average number of patents transferred through licensing in the years that the state adopts IDD.

Table 1. Summary statistics and correlation matrix

	Variable	Obs	Mean	Std. Dev.	Min	Max
(1)	MFF Patents	206,400	2.76	53.31	0	11750
(2)	MFT Patents	206,400	0.94	22.24	0	6119
(3)	Treatment (IDD)	206,400	0.51	0.50	0	1
(4)	Enforceability	206,400	0.46	0.50	0	1
(5)	Internal patents	206,400	2.63	21.02	0	2255
(6)	Sales (log)	206,400	18.79	3.96	0	25.39
(7)	Employment (log)	206,400	7.24	2.98	0	13.88
(8)	Noncompete Index	206,400	4.07	2.09	0	9
(9)	Firm age	206,400	66.63	43.03	21	410
(10)	Firm total internal patent (log)	206,400	1772.07	5054.79	0	43818

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	1.00									
(2)	0.01	1.00								
(3)	0.00	0.00	1.00							
(4)	0.00	0.00	0.15	1.00						
(5)	0.01	0.03	0.00	-0.01	1.00					
(6)	0.04	0.03	0.00	0.06	0.05	1.00				
(7)	0.05	0.03	-0.01	0.06	0.06	0.92	1.00			
(8)	-0.01	-0.01	0.38	0.45	-0.03	0.08	0.09	1.00		
(9)	0.02	0.03	0.01	0.05	0.02	0.37	0.46	0.10	1.00	
(10)	0.01	0.02	-0.02	0.03	0.19	0.27	0.34	0.03	0.17	1.00

Table 2. Key measures and constructs

Measures	Constructs
MFF Patents	External technology sourcing through acquisition
MFT Patents	External technology sourcing through the market for firms
Treatment (IDD)	Exogeneous constraint on the mobility/supply of external employees
Enforceability	Categorize states based on the non-compete enforceability scores developed in Starr (2019)

Table 3. Inventor's patent life within a company (year)

Sample	All	NANO	RNAI
mean	6.89	6.01	6.37
SD	7.16	6.03	6
median	5	5	5
95 pctile	22	19	17

Note:
This is a simple summary statistics for the inventor's patent life (year) within a company. Patent life is measured by the number of years between when the inventor had the first patent and the last patent with a company, dated by the year of initial filing.
Column 1 is the summary statistics for all sample. Column 2 is for firms that have at least one patent on Nanotechnology. Column 3 is for firms that have at least one patent on RNAi.

Table 4. Treatment effect on external technology sourcing at the state-year level

VARIABLES	(1) MFF	(2) MFF	(3) MFT	(4) MFT
IDD		0.25**		0.57***
		(0.14)		(0.28)
Internal patent	0.01	0.01	-0.05*	-0.05+
	(0.02)	(0.02)	(0.03)	(0.03)
Constant	1.52***	1.52***	0.45***	0.45***
	(0.04)	(0.04)	(0.06)	(0.06)
Observations	999	999	999	999
R-squared	0.77	0.77	0.79	0.80
State FE	YES	YES	YES	YES
VCE cluster	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.05$, ** $p<0.1$, * $p<0.15$, + $p<0.20$

Note: The analyses in this table are performed at the state-year level. The dependent variable are the aggregated number of patents transferred through the MFF (1 and 2) and the MFT (3 and 4) in each state-year, respectively. The models control for state-year level internal patenting, state fixed effect and the robust standard errors are clustered at the state level. It shows a positive treatment effect on both MFF and MFT patents.

Table 5. Treatment effect based on different model specifications

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Dep var=log(# of MFF patents)			Dep var=log(# of MFT patents)		
IDD	0.03***	0.05***	0.01+	0.01+	0.03***	-0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
Internal patent	-0.06***	0.00	-0.01	0.09***	0.10***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sales	-0.01***	-0.01***	-0.01***	-0.01***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment	0.07***	0.06***	0.06***	0.03***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm age	-0.00***			0.00***		
	(0.00)			(0.00)		
Noncompete Index	-0.01***	-0.02**	-0.01	-0.01***	-0.02**	0.01*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Constant	0.17***	0.10***	-0.17***	0.05***	0.11***	-0.10***
	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.03)
Observations	206,400	206,400	206,400	206,400	206,400	206,400
R-squared	0.07	0.21	0.22	0.05	0.25	0.26
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	YES	YES	NO	YES	YES
State FE	NO	NO	YES	NO	NO	YES
VCE cluster	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.05$, ** $p<0.1$, * $p<0.15$, + $p<0.20$

Note: This table shows the firm-state-year level assessment of the treatment effect of IDD, based on different model specifications. Columns 1 through 3 look at the MFF patents, and columns 4 through 6 look at the MFT patents. All models control for internal patenting, firm level time-variant variables such as sales and employment, the state level non-compete index, and firm age when firm fixed effect is not applied. Robust standard errors are clustered at the state level. Columns 1 and 4 include year fixed effect. Columns 2 and 5 include year and firm fixed effect. Columns 3 and 6 include year, state, and firm fixed effect. In the subsequent analysis, the last model is selected (columns 3 and 6).

Table 6. Treatment effect on external technology sourcing at the firm-state-year level

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Dep var=log(# of MFF patents)			Dep var=log(# of MFT patents)		
	All	All	Treated	All	All	Treated
IDD		0.01+	0.01+		-0.00	-0.00
		(0.00)	(0.00)		(0.00)	(0.00)
Internal patent	-0.01	-0.01	-0.01*	0.09***	0.09***	0.09***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Sales	-0.01***	-0.01***	-0.01***	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment	0.06***	0.06***	0.06***	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Noncompete Index	-0.01+	-0.01	-0.00	0.01*	0.01*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.17***	-0.17***	-0.13***	-0.10***	-0.10***	-0.13***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	206,400	206,400	131,943	206,400	206,400	131,943
R-squared	0.22	0.22	0.23	0.26	0.26	0.28
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
VCE cluster	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.05, ** p<0.1, * p<0.15, + p<0.20
Note: This table shows the firm-state-year level assessment of the treatment effect of IDD using the selected full model. Columns 1 to 3 look at the MFF, and columns 4 to 6 look at the MFT. Columns 1 and 4 include only controls and columns 2 and 5 also include the treatment variable IDD. Columns 3 and 6 are based on the sample of states that eventually received the treatment. The result suggests there is a 1 percent increase on MFF patents upon IDD treatment, indicating a strong substitution effect. Based on the results, there is no substitution effect for the MFT patents.

Table 7. Comparing states with different levels of enforceability

VARIABLES	(1) MFF	(2) MFF	(3) MFT	(4) MFT
	High	Low	High	Low
IDD	0.01***	-0.00	-0.00	0.01
	(0.01)	(0.00)	(0.01)	(0.01)
Internal patent	-0.01*	-0.00	0.08***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)
Sales	-0.01***	-0.01***	-0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Employment	0.05***	0.06***	0.01	-0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Noncompete Index	-0.00	-0.01*	0.01***	0.00
	(0.01)	(0.00)	(0.00)	(0.01)
Constant	-0.05	-0.23***	-0.07***	-0.14***
	(0.05)	(0.07)	(0.03)	(0.06)
Observations	94,524	111,876	94,524	111,876
R-squared	0.24	0.23	0.26	0.28
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
VCE cluster	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

Note: This table looks at the treatment effect of IDD in different subsamples based on the level of enforceability from Starr (2019). The states are defined to be either high or low enforceability based on the enforceability score. Columns 1 and 3 are for high enforceability and columns 2 and 4 are for low enforceability. The result suggests that the treatment effect is stronger under high enforceability and weaker under low enforceability.

Table 8. Treatment effect estimation based on the matched sample

VARIABLES	(1) MFF	(2) MFF	(3) MFF	(4) MFT	(5) MFT	(6) MFT
	All	High	Low	All	High	Low
IDD	0.02***	0.03**	0.01*	0.01	0.01+	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Internal patent	-0.01**	-0.01	-0.01+	0.08***	0.08***	0.08***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sales	-0.01***	-0.01***	-0.01***	0.00+	0.00	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employment	0.05***	0.05***	0.06***	-0.01*	-0.00	-0.01+
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Noncompete index	-0.00	0.00	-0.01***	0.00	0.01***	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	-0.14***	-0.03	-0.16**	-0.10***	-0.11***	-0.13***
	(0.04)	(0.06)	(0.09)	(0.03)	(0.04)	(0.06)
Observations	210,324	116,487	93,837	210,324	116,487	93,837
R-squared	0.23	0.24	0.27	0.26	0.28	0.30
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
VCE cluster	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15, + p<0.20

Note: This table shows the treatment effect estimation based on the matched sample using propensity score matching. After matching, the sample is more balanced between the treatment and control groups, thus provides a more accurate estimation of the treatment effect. Columns 1 and 4 look at the whole sample, columns 2 and 5 look at states with high noncompete enforceability, columns 3 and 6 look at states with low noncompete enforceability. Consistent with the main analysis, but with stronger treatment effect, there is about 2 percent increase in MFF patents with IDD treatment. The treatment effect is higher when the state noncompete enforceability is high, and is lower when the state noncompete enforceability is low.